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Completed Research Paper

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Abstract

Social networking platforms, such as WeChat and Facebook, increasingly become an important channel for advertising and transaction. Despite the growing importance of social network in facilitating social commerce, there has been limited research focusing on the dynamic implicit communities within the social network.

This paper proposes a framework for gathering business intelligence from one popular social media platform in China (WeChat) by collecting and analyzing social network contents and consumer's interaction networks. It is one of the first studies to our knowledge that identifies and analyzes implicit communities from social media platform for social commerce. We conduct case studies in a relationship-based online social group of WeChat. We first extract and analyze implicit communities, representing interactions among users and product vendors, from a large dataset. This is then combined with interaction-based content analysis to identify position of product vendors from these identified implicit communities. After examining the influence of network properties and community structures on consumer's purchase, we propose a chat log-based content analysis to identify product-related information (including product attribute information, user experience information, social support information, and entertainment information). Finally, by combining those information and network structure, we build weighted implicit communities and calculate the influence of these weighted implicit communities on product vendors' income.

Our case studies demonstrate how to use the framework and appropriate techniques to effectively collect, extract, and analyze implicit communities related to the topics of interest, reveal novel patterns in the interactions and communities, and answer important business intelligence questions in the domains.

Keywords: social commerce, implicit community, social network analysis, content analysis.

Introduction

Since the development of social media, there is an explosion of online social groups on the social network in recent years. The online social groups allow users to post content and conduct informal communications with others conveniently. Group members can chat about personal opinions, stories, perceptions, jokes, social supports, etc. By chatting with each other, social links and interaction contents are generated among them and dynamic implicit communities were formed. For enterprises, those online social groups not only served to facilitate the communication between vendor and consumer, but also become an important tool for network marketing and social commerce. At the same time, in recent years, the way of network marketing has been gradually shift from direct advertising to in-depth social communicating. Enterprises actively build social groups to interact with potential consumers (Khansa et al. 2012).

In recent years, there is quite a lot of research that focuses on how can online reviews facilitate customer's purchase intention (Aggarwal et al. 2012; Amblee and Bui 2011; Benlian et al. 2012; Chevalier and Mayzlin 2006; Fan et al. 2012; Forman et al. 2008; Gu et al. 2012; Riegner 2007; Zhang et al. 2014; Zhu and Zhang 2010). This research stream intends to argue that this kind of formal information can significantly influence purchase intention and guide practitioners with their propositions. At the same time, formal communication between vendor and customer, such as interacting with customers by using official account in MicroBlog, has been highly valued in previous research. The formal communication enabled the exchange of product attribute-oriented information and experience-oriented information between seller and customer. However, we argue that related informal communications, such as chatting and telling jokes, can better attract customer's attention and arouse their purchase intention and then facilitate actual purchase behavior.

A rich literature exists which discusses websites-based online purchase intention (Goh et al. 2013; Schlosser et al. 2006), such as Amazon.com (Amblee and Bui 2011; Chen et al. 2011; Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2009; Gu et al. 2012), rare are concerns the actual purchase in mobile instant messaging (IM) applications. However, since the high mobility and responsiveness, mobile IM apps are becoming indispensable in individual's daily life. Take the WeChat (a famous mobile IM app in China) as an example, some people are becoming rely on WeChat to do daily online communication and moreover do commercial interaction base on the social network formed by using WeChat.

Note that members of an online social group are dynamic and are frequently updated. They can join in or left any time make the general structure of the online social group dynamic. Meanwhile, the temporal linkages between members (implicit community), which represent the interactions between members at a particular moment, are also dynamic. For example, some group member will dive and keep quite when the current topic is not attractive to him/her, which make this member isolated at that moment even though he/she have general relationship with others (e.g. they are group members of a same social group). Therefore, it's important to study the social structure of implicit community and understand how the present social links of participants influence their consumption decisions.

This study aims to examine consumer's purchase behavior within an online social group by analyzing the communication contents of its stakeholders (e.g. customers or participants). In addition, by analyzing characteristics and dynamics of potential implicit communities, it is possible to study the social network structure of online consumer networks and identify its influence on consumer's purchase behavior (Chau and Xu 2007). These insights enable companies and organizations to make better decisions on social commerce strategies (Kozinets et al. 2010; O'Leary 2011).

Literature Review

Some activities on social networking Web sites are not commercial in nature. For instance, people share their thoughts, information about a news event, photos, and jokes for amusement. These, albeit popular, cannot be identified as social commerce because these activities do not lead to any commercial benefits such as buying or selling products or attitude changes on certain commercial events. Therefore, it is essential that information sharing or other activities of social media involve commercial intentions and implications. To define it broadly, any kind of activity that leads to commercial benefits falls into the definition of commercial activities. The concept of consumer buying behavior is not new. It refers to the decision making process which evolves in multiple steps including the act of buying and using products and services. Studying consumer purchase behavior helps in understanding the influential factors on purchase decisions, and answers the question of why customers buy what they buy. It also enables firms to comprehend the reaction of customers to their marketing strategies. Understanding why, where, what, and how customers buy can gives a better prediction of customers' response.

Older business models dealt with one-to-one interactions resulting in the development of customer-seller relationships (Dwyer et al. 1987). But social networks transformed customer-seller interactions from being one-to-one to community-based (Stephen and Toubia 2010). Hence, the newer business models had to rely on community-based communications (Yang et al. 2006; Zhang et al. 2009).

Recently, research on community-based social commerce revolves around increasing business revenue using individual word-of-mouth distribution and advertisement techniques (Olbrich and Holsing 2011; Trusov et al. 2009). However, it is unclear whether characteristics of the community have impact on business revenue. Social groups are specific social networks that enable assembled members to gather together as an intangible circle to share information and social support {Formatting Citation}(Anderson and West 1998; Dholakia et al. 2004). Member in social group make purchase decisions mainly base on interpersonal social activities and personal cognitive perceptions rather than precisely scrutinize product attributes or do a tradeoff between monetary cost and benefits (Bagozzi et al. 2006; Tsai and Bagozzi 2014). Consequently, the environmental features of social groups are important in influencing group members' purchase intention (Animesh et al. 2011).

Studies on consumer purchase behavior in social commerce mainly focus on three aspects: individual characteristics, word of mouth, and social interaction(Animesh et al. 2011; Chen et al. 2011; Cheung and Thadani 2012; Guo and Barnes 2011; Tam and Ho 2005). Among that, the research about individual characteristics and word of mouth transplant and expand the traditional e-commerce consumer behavior research, which does not reflect the nature of social commerce. Social interaction as an essential element of socialization has received the researchers and practitioners' extensive concern. Social interaction in social commerce mainly has two forms: 1. Interaction between consumers and vendors in a form of vendors leading communication. For example, the vendor post product information, and consumer rating or provide feedback. 2. Interaction between consumers, for example, the consumers' discussion, information exchange, recommendation and feedback of specific products. The first kind of interaction has been widely used and comprehensively studied in traditional e-commerce. The second kind of interaction is a new and distinctive kind of interaction in social network. Since the diversity of interaction between consumers, the commercialization of social interaction is still a new business model which has not been studied in detail.

Group members are connected dynamically in online social group through posting, commenting, feedback, "@", forming different temporally social networks of members, which called implicit community. Implicit communities refer to the social network formed temporarily by the interactions among group members (Chau and Xu 2007). When a group member joins an online social group, he/she already has general relationship with other group members as they are in the same group. However, an implicit relationship exists only when the group member has some contact with others, such as @, feedback, comment, broadcasting, etc. Rather than general relationship, this implicit relationship emphasizes social interaction among members (Erickson 1997).

Social network analysis (SNA) is an appropriate method to study the social structure of implicit community. In particular, the implicit relationship of online social group usually hiding in chatting content, therefore makes a content analysis-based SNA useful for identify the implicit community by extracting chat-log data from online social groups.

The Framework for Analyzing Implicit Community in Online Social Groups

In this section, we present a framework adapted from Chau and Xu (Chau and Xu 2007) for conducting implicit community identification and analysis of consumer's purchase behavior. Our framework, shown in Figure 1, consists of the following steps (components):

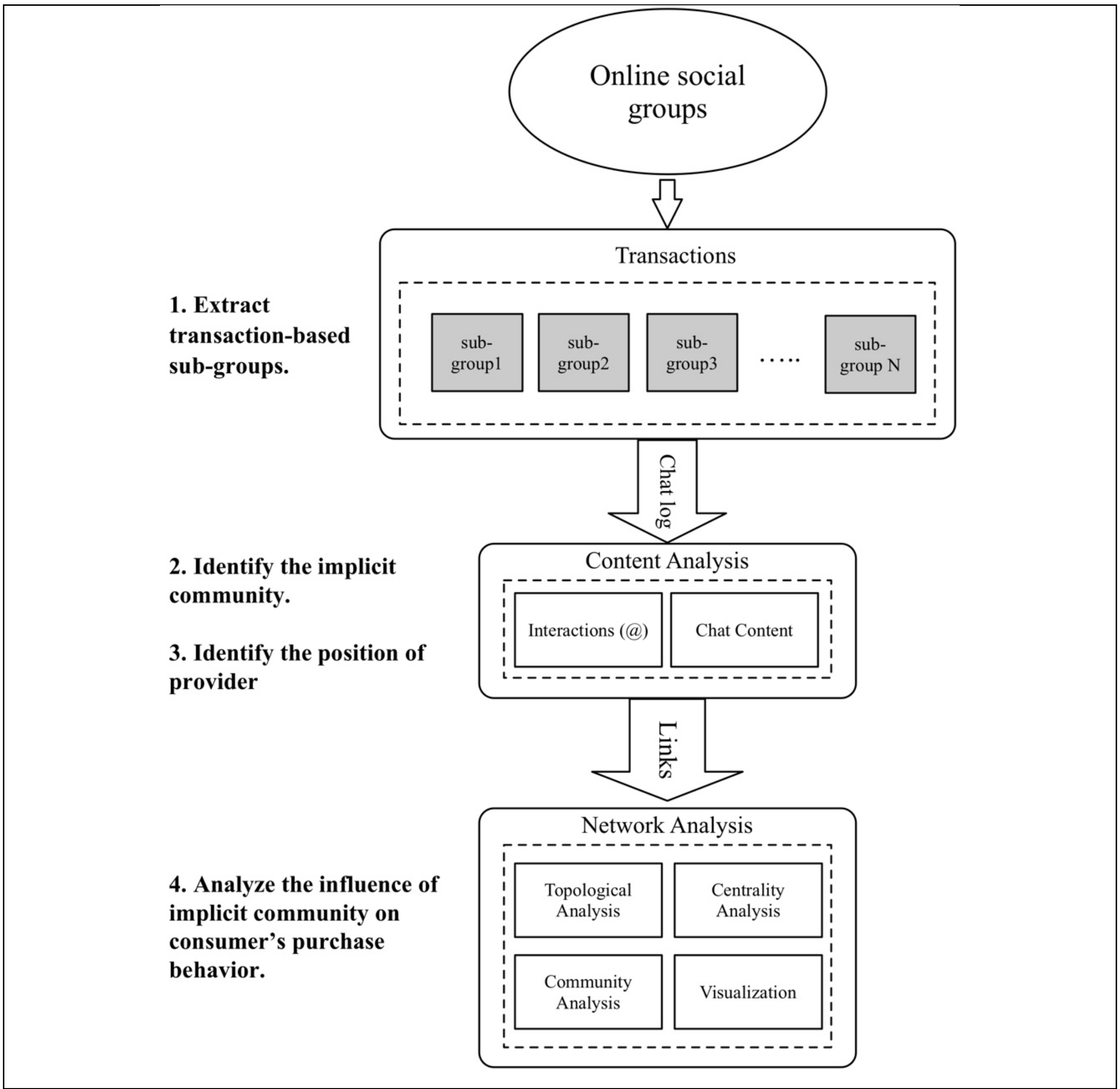

Figure 1. Research Framework

Step 1. Extract transaction-based sub-groups.

This study aims to identify consumer's collaborative purchase behavior within an online social group in IM platform. Due to the chat room characteristics of IM apps, member can only view limited content since the screen will be flooded by updated content. Therefore, group member will take a collaborative purchase behavior (e.g. word chain) in case the product provider omits someone's order (Sun et al. 2016). An example of word chain is as follows:

Top red wine from Australian winery. Who wants to buy please Solitaire: 1 Li Jialin 2 Bottle; 2 Miao Fung East 1 Bottle; 3 Wen Gong 3 Bottle....

This is a transaction of red wine, while "*Top red wine from Australian winery, who wants to buy please Solitaire*" is the title of this word chain. Those who want to buy the red wine should add his/her name and order one by one to the word chain. Finally, a word chain of all the consumptions will be formed. A complete transaction starts from the first time product provider post the Solitaire title and end when the last consumer adds his/her order. All the chatting content in the transaction process will be extracted and those participants will be regarded as a sub-group.

Step 2. Identify the implicit community.

After dividing the online social group, one can begin finding the implicit communities in those sub-groups. These implicit communities are represented by social interactions among group members center on particular kinds of products. Due to informal structure of chat-log data, group member may use different nickname or ID to represent a same person. It is better to use manual content analysis to retrieve community information and membership relationships. This study manually read the description and content of those implicit community to ensure relevance, authenticity, validity, and suitability of data. Implicit community can be extracted by identify group member's "@" behavior, which indicates a communication behavior among group members. As some group member just write others' name without add an "@" when communicating. A manually scrutinize the chatting context and messages is needed to find slipped relationships. After that, topological, centrality, and community analysis, will be applied to the implicit communities to find valuable patterns.

Step 3. Identify the position of provider.

Previous literature pointed out that position of product providers will influence their sale volume. For example, a popular group member (higher in-degree) will get more attention and trust, which facilitate their marketing behavior. Degree is defined as the number of links incident upon a node and it can be calculated to indicate the providers' position within the implicit community.

Step 4. Analyze the influence of implicit community on provider's income.

For each transaction, provider's income can be calculated. Meanwhile, visualization programs can be used to display a graphical notation of the implicit community. A comparison analysis of different implicit community will be applied to analyze the relationship between community pattern and provider's income.

Case studies

Data Set

We choose an online social group in WeChat as our source of data. WeChat is the most popular social platform in China and has prominent features to support social grouping, and these features are useful for product providers to keep casual communications with consumers. This online social group has 479 group members (The maximum number of a WeChat group is 500). It is a relationship-based group while all the group members are EMBA students from the same school in China. Most of them are CEO or senior managers of a company. Any of the group member can be provider if he/she have products or be a consumer likewise. The statistics of this group is shown in Table 1.

Age	Ratio	Income (ten thousands)	Ratio
Below 26	0	0~2	3.8
26~30	0.8	2~4	22.1
31~40	30.3	4~6	19.7
41~50	57.3	6~8	12.4
51~60	10.5	8~10	4.5
61~70	1.1	10 以上	37.5

Table 1 Statistics of the WeChat group

Step 1. Extract transaction-based sub-groups.

We export all the chat-log data from WeChat (2013 November to 2014 March) and identify the implicit online consumer communities from the chat-log data (about 150,000 chat records). We first searched for each trade that contained real transactions in the chat-log and retrieved Top 10 sub-groups with higher income. Product can be divided into three categories: food, domestic implements, service activities. For each sub-group, we read all its chat-log data and description of the product and classified its product types. In order to eliminate the disturbance of product type, we discarded 3 sub-groups (2 domestic implements and 1 service activities) and finally get 7 sub-groups. We also studied the degree distributions of the networks and calculated average degree, highest in-degree and highest out-degree by using Gephi. The statistics of Top 7 profitable sub-groups are shown in Table 2.

No.	Nodes	Units	Product	Income	Average Degree	Highest In-degree	Highest Out-degree
1	134	1248	Red Wine-fcb	1080000	3.143	64	16

2	197	1089	Red Wine	805000	5.882	37	54
3	126	1695	Olive Oil	639660	4.103	28	44
4	128	540	Sea Cucumber 1	362928	4.797	22	20
5	86	644	Enzyme	191560	3.766	17	21
6	241	5124	Tea	98938	4.145	16	21
7	118	884	Sea Cucumber 2	83520	4.639	19	18
Nodes=number of participants; Units=number of chatting messages;							

Table 2 Statistics of Top 7 profitable sub-groups

Step 2. Identify the implicit community.

We further examined the content of the transaction periods by extracting all the sentences. The interaction networks are the networks constructed by the interaction relationships between group members extracted from the collected sub-groups. As mentioned in the previous section, we identified two types of interactions among group members: @, which occurs when one group member talk directly to another (one or more) group member, and chat with someone without using @. Group member may also broadcast messages. However, broadcasting in a group is similar to contact all the other people and build relationship edges between them. Therefore, this study didn't count the broadcasting behavior. Note that none of these sub-groups contains all of the 479 group members in our data set. This is because some group members (diving participants) have no interaction relationships with anyone else in this particular data set. They are isolated nodes and are not included in the networks.

Step 3. Identify the position of provider.

It is important to identify the position of provider who play important roles in information dissemination in the implicit communities. To identify the position of product provider. We calculated in-degree, out-degree. The statistics of the 7 implicit communities and centralities are as follows (Table 3):

No.	Nodes	Links	Product	In-degree	Out-degree
1	134	220	Red Wine-fcb	62	1
2	197	547	Red Wine	28	54
3	126	437	Olive Oil	17	9
4	128	319	Sea Cucumber1	22	0
5	86	145	Enzyme	3	18
6	241	172	Tea	0	21
7	118	276	Sea Cucumber2	13	2

Table 3. Statistics of implicit communities

We first examined the in-degree (the number of incoming links) and out-degree (the number of outgoing links) of the product provider. A group member with a high in-degree usually is popular or "authoritative" (Kleinberg 1999). For example, a large number of incoming interaction links implies that the group member is somehow liked or endorsed by others who conduct a direct interaction to him/her.

We found that the highest value of in-degree in the interaction network was 62, which come from the provider of Red Wine-fcb (see Table 3). Also, he is the provider earned the most in this online social group. The high out-degree group member, in contrast, may not be popular. Instead they may be "drainages" who can direct others' intention to the product, and thus are also quite important to identify. It shows that provider with higher in-degree are relatively earned more in the online social group. For those provider who has lower in-degree, out-degree matters a lot, which means that provider should keep in touch other group members actively if they want to gain benefits from the group. The visualization

There are two providers have the same degree (Enzyme and Tea). However, they have different ratio of nodes and links. It shows that Enzyme has higher Links/Nodes ratio, which means that in this transaction process, group members are more active in communicating with others.

Step 4. Analyze the influence of implicit community on provider's income.

In order to understand the influence of implicit community pattern on provider's income, we performed comparison topological analysis on two pairs of implicit communities (sell the same product: red wine and Sea Cucumber). We decide to compare these two implicit community is because providers sell the same kind of product, which will eliminate the disturbance of factors other than social structure. A visualization of these implicit communities is shown in Figure 2-5. The Red node indicates the product provider, while grey nodes indicates other participants.

Red Wine Comparison

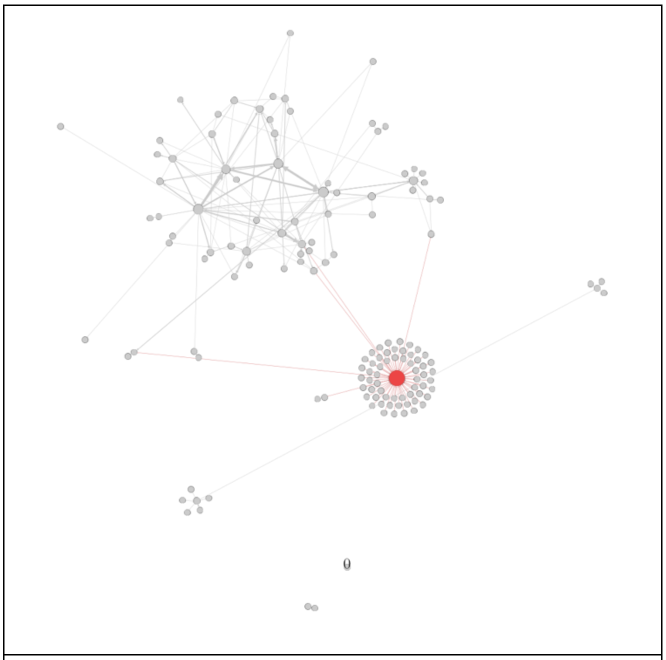

Figure 2 Red Wine 1 implicit community structures

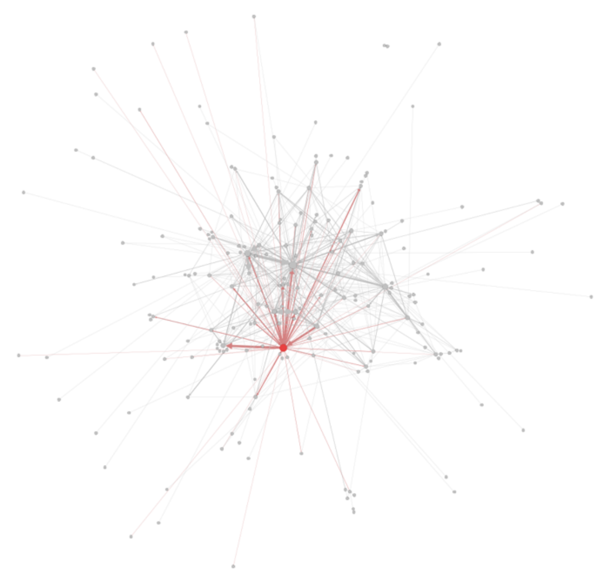

Figure 3 Red Wine 2 implicit community structures

From the comparison figure, we can see that:

It is clear that the seller of red wine 1 has a personal social circle in the implicit community, which means that he has a certain degree of leadership and has a certain number of supporters. While the seller of red wine 2 is relatively at the edge of the network, and there is no obviously cluster around her.

Sea Cucumber Comparison

Figure 4-5 represents the implicit community structure of sea cucumber transaction.

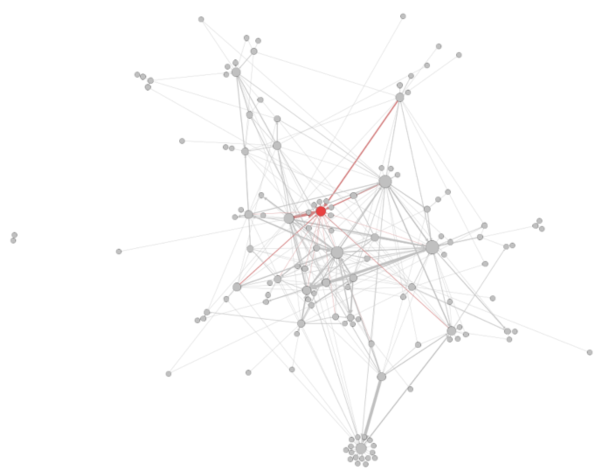

Figure 4. Sea cucumber 1 implicit community structure

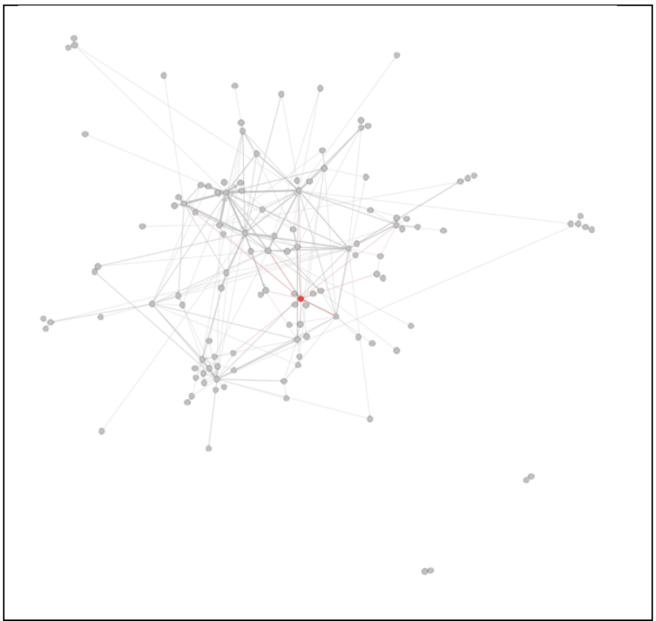

Figure 5. Sea cucumber 2 implicit community structure

The implicit community of sea cucumber 1 has higher link/node ratio than sea cucumber 2. Meanwhile, provider has higher degree when he sells sea cucumber 1. From these two figures, we can also see that implicit community of sea cucumber 1 has a relatively more centralized structure with thicker links than sea cucumber 2. It also has more distinct clusters, which enables efficient dissemination of social influence.

Discussion

In this section, we discuss our findings with an aim to answer the questions raised regarding the implicit communities of the online social group. These implicit communities are more meaningful because consumers and product providers have actually social interactions with each other.

In this study, we first extract transaction-based sub-groups from the chat-log data. Second, we code the social interaction as implicit communities and finally get 7 representative implicit communities. Third, we calculate the characteristics of those implicit communities and the position of product vendors. Fourth, we compare two pairs of similar products and explore the influence of social structure on consumer's purchase behavior, which represented by product sales.

Our results verified that a simple analysis of the general community would miss the underlying influence of actual social structure in the marketing process. As suggested by our framework, analysis of implicit community is necessary to reach the potential consumers and examine the influence of social network structure on consumer's purchase behavior.

In the case study, we analyze the social interaction between group members. Patterns of implicit community was found in the data set. The results indicate that popular group member (higher in-degree) will gain more from marketing process within an online social group. Whereas, for those provider who has lower influence power, it's also possible to raise their benefit by actively communicate with other members. This study shows that, although consumers may not necessarily familiar with a product or provider in personal, the implicit community can provide potential power for influence their purchase decisions.

In the implicit community that gain more benefits we found gathered cluster around the provider. Whereas, in those implicit communities that product providers gain less benefit we found a less centralized structure. This result shows that the decentralized structure eliminates the possibility that the implicit community may help shaping potential consumers' purchase behavior. Therefore, it is important to build personal clusters within an online social group, which may enhance the social support from the members of this clusters.

Our study extends research in social network analysis by proposing a framework for identify implicit communities from informal textual data of online social group. We are among the first to link implicit communities to consumers' purchase behavior. Our elasticity results add further evidence to the view that social structure of implicit communities is a critical factor for influencing consumer's purchase behavior.

This work also indicate that assess the social structure of implicit community may be useful for understanding purchase behavior in online social groups. For practitioners who want to promoting in online social groups, according to the results of step 3, a key strategy for them is to enhance their popularity, namely, in-degree in this study. When it's not easy to be a popular one, it is better to be an active one who interact actively with others, especially the popular one. Besides, according to the results of step 4, it's better to join a centralized cluster in which information will be transmitted faster than a decentralized one. Overall, our findings yield preliminary insights for marketers so that they can better arrange their activities to boost sales.

Limitations

Our research has several limitations. First, we collected data in only one social network platform, WeChat, which contains primarily social-focused online groups. This may not be applicable to other interest-oriented or company-centered groups. Therefore, caution should be taken when applying the results of the current study to other online social groups.

Second, the focus of our research is to analyze the influence of implicit communities on consumers' purchase behavior in online social group. There are also many other social networking platforms (e.g. Microblog, SNS) that enable consumers to conduct direct consumptions. As different platform has different technical features for supporting social interactions, the social structure in those platforms may be different depending on the specifics of those platforms. Therefore, the influence pattern of implicit community on consumers' purchase behavior may not applicable to other social networking platforms.

Third, many group members of this online social group have the channel to provide products, which makes this group appropriate for social commerce. For those online social group, in which group members are only consumers, the pattern of implicit community may be different.

Conclusion and Future Research

Our research has several implications. In this paper, we present a framework for identify implicit communities within an online social group and collect chat-log data to analyze the influence of implicit community on consumer's purchase behavior. The content analysis and network analysis methods can be extended to other studies.

Second, we found that different implicit communities resulted in different level of provider benefits. A provider with higher in-degree are likely to gain more benefit compare to provider with lower in-degree. Meanwhile, a centralized implicit community provides strong influence in shaping consumers' purchase behavior. The current study has provided some insights into the research of social commerce.

This study focus on the influence of network structure on consumer's purchase behavior and relatively concern less on the interaction content of group members. In future research, a content analysis of product information or experience information generated by group member can be studied.

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